A REVIEW OF THE APPLICATIONS OF SAR POLARIMETRY AND POLARIMETRIC INTERFEROMETRY – AN ESA FUNDED STUDY

D G Corr [(1)], S R Cloude [(2)], L Ferro-Famil [(3)], D H Hoekman [(4)], K Partington [(5)], E Pottier [(3)] and A Rodrigues [(7)]

[(1)] QinetiQ Ltd, Room 1004, A8 Building,, Cody Technology Park, Farnborough, Hants. GU14 0LX, UK
Email:dcorr@qinetiq.com
[(2)] AELc, Granary Business Centre, Unit 3.3, Fife. KY15 5YQ, UK
Email: scloude@aelc.demon.co.uk
[(3)] IETR, Université de Rennes I, Bât 11D, 263 Avenue Général Leclerc, CS 74205, 35042 Rennes Cedex, France
Email: laurent.ferro-famil@univ-rennes1.fr
Email: eric.pottier@univ-rennes1.fr
[(4)] SarVision AV, Oudlaan 37, 6708 RC Wageningen, The Netherlands
Email: info@sarvision.nl
[(5)] Vexcel UK, Arrowfield House, Newbury, Berkshire. RG14 6AA, UK
Email: Kim.Partington@btinternet.com
[(7)] QinetiQ Ltd, Room 1058, A8 Building, Cody Technology Park, Farnborough, Hants. GU14 0LX, UK.
Email: afrodrigues@qinetiq.com

ABSTRACT

This paper presents a literature review conducted under an ESA funded study entitled "Applications of SAR Polarimetry". This study was jointly conducted by QinetiQ, AELc, University of Rennes 1, SarVision and Vexcel UK. The overall study aim was to review, assess and validate the benefits of using polarimetry for land cover classification and sea ice classification. The potential of polarimetric interferometry for vegetation parameter retrieval was also assessed and demonstrated. A literature review on classification techniques for polarised SAR data was undertaken. The objective of this review was to choose the most promising techniques prior to their evaluation for land and sea ice applications. This paper presents the objectives, the key issues, the conclusions and recommendations of the review.

1 STUDY BACKGROUND

The objective of this study is to investigate techniques that will support applications of SAR polarimetry in ESA missions in the Earth Watch programme, and also missions in which ESA has a strategic interest such as Terrasar, Radarsat 2 and Alos Palsar. In particular, to investigate techniques for the following application areas: agriculture and land use classification, sea ice monitoring. Additionally, the applications of the new technique that combines SAR polarimetry with SAR interferometry (POLinSAR) are also investigated.

The selected application areas are important. The mapping of agricultural crops and land cover has been identified by both commercial service providers and by the European Commission as a key product area. Sea-ice classification, for navigation, is already effectively an operational application with current sensors, i.e. single frequency and single polarisation SARs. However the use of polarimetric data is anticipated to resolve ambiguities that can arise with single channel data.

Polarimetric data can also provide information on physical characteristics such as soil moisture and forest bio mass. When polarimetry is combined with interferometry further information becomes available such as tree height.

In order to study the wide rage of polarimetric topics involved the following consortium was formed:
QinetiQ Ltd (Prime Contractor), AELc, SarVision BV, University of Rennes and Vexcel UK Ltd.

This paper describes the results of a literature survey on techniques for the classification of polarimetric data. This survey provides a background to specific areas that are presented separately at this Workshop [1, 2, 3], it also provides a summary of the basic issues and problems that arise in the classification of polarimetric data which are relevant to the round table discussions. Polarimetric interferometry is a largely self contained new technique and is described in [4]

2 INTRODUCTION TO LITERATURE REVIEW

This literature review for land applications of polarimetric Synthetic Aperture Radar (SAR) covers the period 1989 to November 2001. The objective of the review is to provide a critical review of polarimetric classification techniques for agriculture and land cover applications.

SAR is an important sensor for Earth observation as it is unaffected by cloud cover and operates independently of solar illumination. In order to apply the sensor effectively to user applications, it is necessary to be able to distinguish between different types of land cover and surface conditions. Further, it is also desirable to be able to measure properties of the land cover such as biomass, soil moisture and surface roughness.

If single frequency monopolarisation systems are used, there is generally a considerable degree of ambiguity between different types of land cover. To overcome this, the dimensionality of the observation needs to be increased. This can be achieved through the use of multiple frequencies and/or multiple polarisations. (Multi-temporal and multiple incidence angles are other ways of increasing the dimensionality of observation, but are not be considered here.)

The radar interaction with land cover changes according to frequency. Components of vegetation that are much smaller than the radar wavelength have little interaction with the radar. For example, at L-band radar can penetrate a forest canopy down to the forest floor, whereas at X-band scattering is principally confined to the forest canopy.

The radar interaction with land cover also changes with radar polarisation. The interaction depends on the shape and orientation of the scatterers and the scattering mechanisms (i.e whether it is single or multiple scattering). The radar *signature* depends on the interaction and on whether the scatterers are principally of one type or a mixture of several types. In general, different polarisations will produce different signatures, only fully polarimetric observations can capture all the information. There are some applications however, where features from a partially polarised system are *sufficient* for classification. However this would not be known beforehand without experimental or theoretical evidence.

Over the last 20 years there has been considerable progress in the application of multi-polarimetric data to land observation. There have been three complementary lines of development in the following areas:

- Polarimetric radar data collection and calibration
- Techniques for describing polarimetric radar signatures
- Techniques for the classification of polarimetric radar imagery

Without the data provided by systems such as AIRSAR, SIR-C and E-SAR both applications development and theoretical developments would not have been possible.

This review begins by describing the key issues in the classification of SAR data. It then provides an overview of the key developments in classification techniques that address these issues. Over 50 selected references were initially consulted, only the most significant or representative ones are quoted in the references.

A critical appraisal of the techniques then follows. This addresses three areas:

- The polarimetric features
- Speckle reduction
- Classification

The appraisal concludes with the recommendations for the study.

For completeness, current trends in classification are also discussed. Finally the conclusions of the survey are presented.

3 REVIEW

3.1 Key issues in the classification of SAR data

There are technical problems and conceptual problems associated with image classification. The technical issues have undergone progressive developments over a number of years. The conceptual issues have always been present, but have generally been masked behind classification errors and the effects of data resolution. Both of these issues are introduced below.

In classification there are essentially two fundamental technical problems to be addressed. The first is to identify the parameters that capture the information from the radar signatures, which will allow different land cover classes to be distinguished from each other. The second is to devise a general technique that uses these features to distinguish classes in complex scenes.

Specific features may be used for particular investigations or the total signature, as represented by e.g. the covariance matrix, may be used for all investigations. Any features derived from the image data will be affected by speckle. Speckle is a random variation in the signal amplitude of distributed targets that arises from the random phasor sums in the coherent imaging process. There are effectively two strategies for speckle effects to be reduced or removed, either by its removal prior to the formation of the features, or by producing features through a process that also reduces speckle (e.g. neighbourhood averaging).

There are basically two approaches to classification: unsupervised and supervised. Each method has advantages and disadvantages. It will be seen that in practice these approaches complement one another.

There is also a problem that arises from the inexactness that may be inherent in many user applications. This is to do with the concept of what a classification is meant to represent. In many user applications a single user class is a mixture of several classes of objects. The mixture may contain distinct classes or classes that are relatively similar. An example of a mixture of distinct classes is the class "urban", this is really a super class that consists of buildings, roads, grass, trees etc. An example of a mixture with several relatively similar classes is a woodland with trees of different species. Indeed even a single species may exhibit within class variations e.g. due to health, age. In addition to the *types* of scene just described, low system resolution is an important factor that also gives rise to mixed properties in remote sensing measurements. All of these issues need to be *recognised* in the design, operation and validation of a classification scheme.

In view of the factors described above it is clear that the likelihood of a successful scene classification depends on the complexity of the scene and the within class variations that are present.

3.2 Key developments in scene classification

The status of polarimetric measurements in 1990 is comprehensively described in the book by Ulaby and Elachi [5], which brings together developments over the previous decade such as [6,7]. This book shows that there is considerable potential in polarimetric radar data, but that the techniques for extracting information had not yet been developed. The fundamental issues to be resolved were in the following areas:

- Definition of the features derived from the polarimetric signatures that contain the information relevant to classification
- Determination of the feature statistics for use in the development of maximum likelihood classifiers.
- Speckle reduction techniques that do not destroy the inter channel relationships in polarimetric data in terms of phase and amplitude

Initially researchers experimented with many features (such as channel intensity, channel ratios, channel phase difference etc.). The feature combinations that best suited their *requirement* were found by experiment [e.g. 8]. This procedure can however lead to practical sets of features for *specific* applications [e.g. 9, 10].

The polarimetric properties of natural objects can also be described in terms of the co-polar and cross-polar response diagrams [7]. However these diagrams are not unique and not amenable to simple comparison or for use as a characteristic measurement.

In 1994 Lee [11] used Wishart statistics to describe the statistical variation of the amplitudes of the terms of the covariance matrix of polarimetric data. This allowed a maximum likelihood classification scheme to be developed using averaged covariance matrices.

The difficulty in the *general* discrimination between different crop types lead to a systematic hierarchical classification scheme [12], however this approach was not developed further.

A new type of general approach was required that could utilise all the polarimetric information, this came through theoretical developments in radar polarimetry.

Techniques for the interpretation of polarimetric signatures have been the subject of considerable research. There are two signature categories in practical applications, determined by whether the scattering objects are stochastic or deterministic. Natural scenes consist of areas containing scatterers of a similar type for example, fields and forests. The stochastic scattering characteristics of these scenes are described by averages of second order parameters, such as the covariance matrix. In contrast man made objects with fixed discrete scatterers (such as ships), are best characterised at a pixel level [13].

In 1996 Cloude and Pottier [14] found that polarimetric characteristics of stochastic objects can be described principally in terms of two parameters H (entropy) and alpha, that respectively describe the purity and type of scattering mechanisms. An additional parameter, A (anisotropy), provides further information on the number of scattering components. Using physical arguments, the H and alpha parameters can be used to provide a basis for a direct classification of polarimetric data [15]. The A parameter can be used to provide further class refinement [16].

There are two approaches to scene classification: unsupervised or supervised. The supervised approach requires ground truth. However it may lead to ambiguities because the scene classes required by the analyst may not necessarily be supported by the properties of the data. Unsupervised classification leads to an understanding of the class separability in the scene that is supported by the polarimetric signatures of the data. A difficulty with unsupervised classification is that convergence depends on the initial seeding of candidate classes. A way to seed the candidate classes is to use class centres defined by the H alpha properties of the data [17].

To improve class definition the statistical variation in stochastic data due to speckle needs to be reduced. A fundamental problem with speckle reduction techniques that use averaging, is the reduction of resolution and the attendant smearing of line features in the data. In [14] Lee overcame this by using an adaptive windowing technique allowing line features to be preserved. This technique can be applied in conjunction with other analysis processes (e.g. H alpha analysis).

An alternative approach to speckle reduction is based on simulated annealing. This technique was introduced in [19] to provide an optimum approach to speckle reduction in single channel SAR images. A problem inherent to the original approach is a small bias that occurs in the annealed data. A practical problem is that computer-running times can become prohibitive. This technique has been adapted in [20] to remove the speckle from polarimetric data. The result of this is that within class parameter variations are revealed.

In 2001 Lee showed that by the use of supervised classification and a Wishart classifier, high classification accuracies for various land cover types could be obtained [21]. This approach could also be modified in a consistent way, for the classification of partially polarimetric data. Good results were reported, this lead to the recommendation of this technique for use in this study, together with the unsupervised method [16] for scenes where there is no ground truth.

4 CRITICAL APPRAISAL

4.1 Speckle

In simple methods of speckle reduction by averaging the covariance data, a reduction in speckle is achieved at the expense of a reduction in resolution. This is undesirable in many applications. With recent techniques speckle may be reduced without altering the polarimetric data characteristics or linear image features [18].

The effect of speckle on the separation of classes has been shown in [10, 20]. In [10] the effect of the number of looks on classification error was studied; depending on the data used several hundred looks were required to reach satisfactory accuracy. In [20] it is shown that simulated annealing techniques can reduce speckle significantly, to reveal the extent of within class variations. It is clear that speckle does lead to ambiguities and that it should be reduced as far as is practicable. It would not be practicable to apply the method in [18] to achieve a similar amount of speckle reduction as in [20].

4.2 Features

4.2.1 Introduction

There is no consensus on the best features to use for general classification. When fully polarimetric data is available there are effectively two approaches for feature selection: one in which features are selected on physical grounds or by practical experience, and the other in which the whole polarimetric signature expressed as a covariance (or coherency) matrix data is used.

4.2.2 Selected features

The use of selected features has been the historical approach [6, 8, 9, 10, 22]. There are two fundamental problems with this approach: how to weight the information, particularly when it is of a different type, and to describe the statistical behaviour of the features in a way suited to the formulation of a maximum likelihood classifier. For example in [22] the features used are $|HH|^2$, $|VV|^2$, $|HV|^2$ and $HHVV^*$ and $\arg\left(HHVV^*\right)$, expressed in logarithms; a Euclidean distance measure was used in unsupervised clustering. These types of features are heuristic and consequently there are many possibilities. There is no direct means to determine the best solution, good features are determined through experience and on physical grounds [e.g. 9, 10] or by systematic selection and reduction [8].

An example of a validated classification scheme using features selected on physical grounds is [10]. This is a practical classification scheme, established for a particular application (forestry). It is based on features that have been found to provide a significant differentiation between classes. These include the backscatter intensities, the HH VV phase difference and complex correlation. These features are sufficient for this application and work well, however the number of classes within a typical scene is small.

4.2.3 Full covariance or coherency matrix

In [21] the whole covariance matrix for the polarimetric data is used. This approach also allows the amount of information to be systematically reduced from fully polarimetric to dual polarimetric, with both real or complex data. The classification method is a supervised method, using a distance measure based on Wishart statistics. This procedure is unified so that results can be compared for full and partial polarimetry. It is reported that, with a few exceptions, fully polarimetric data yields the best results over an agricultural and forest scene. A possible drawback to this unified general approach is that the information may not be weighted in an optimum way to give the best classification results. For example, the channel phase differences or correlation may provide better classification information if obtained explicitly, rather than by being contained within the covariance data. Parameters like correlation can also be normalised.

Similar comments can be made about the unsupervised classification technique of [16], which begins with the full coherency data (the covariance and coherency matrices are simply related).

4.3 Classification

4.3.1 Introduction to classification schemes

There are two approaches to classification depending on whether it is pixel or region (segment) based. In the pixel based methods, features are derived on a pixel by pixel basis (although local neighbourhood averaging may be performed). The agglomeration of these pixels into regions may take place in a post processing operation, but it is not normally a part of the process.

In segment based methods, neighbouring pixels that are in a sense similar are defined to produce regions (segments). Properties are determined that represent the whole region. This method avoids the smearing of properties that result from neighbourhood operations near boundaries. Although the number of pixels per segment is variable, the properties of each segment are determined in an optimal way by the use of all the data available for that segment.

4.3.2 Pixel based schemes

Unsupervised classification requires the initiation of class centres. The difficulty in doing this is to decide how many classes there are and what their parameters are.

The polarimetric decomposition parameters H, alpha and A provide a way to partition the *polarimetric* feature space in a logical way [17]. Whether or not this provides the correct number of class centres for the scene cannot be generally determined. Rules [17] can be introduced to split classes (e.g. if they contain too many pixels) or to fuse classes together (e.g. if they contain too few pixels). However there is a danger of imposing incorrect class structures if the rules are too simplistic (e.g. just based on cluster size); in general expert rules will be required that take into account the scene context.

There is also a possible source of error with this method [17] of initiating the class centres, because the polarimetric decomposition parameters are independent of the absolute scattering level. Therefore separate classes of objects with the same polarimetric characteristics but with different intensity are not recognised.

Supervised classification [21] can be performed if there is ground truth available. This will directly specify the characteristics of a class, however these characteristics may not be unique and consequently ambiguities are built into the classification process.

In both supervised and unsupervised classification Wishart statistics have been used [17, 21] to provide a maximum likelihood decision rule on the class occupancy of image pixels. These are statistics that describe the *amplitudes* of the elements in the covariance or coherency matrices. However, phase information within polarimetric data plays a direct part in the broad characterisation of scattering processes (e.g. in single and double bounce interactions [6, 23]). A fundamental issue that has not been *directly* investigated is the extent to which the use of a decision rule based on amplitude statistics confuses information from inherently different classes, as described by their phase characteristics.

The criterion for assessing the inter-class distance described in [17] is a heuristic parameter whose use has not been justified.

4.3.2 Segmentation based schemes

The essential feature of a segmented image is that it has been divided into regions in which the pixel properties are similar; it should be noted that a segmented image is not necessarily a classified one. In general, there needs to be an additional process that assigns segments with similar properties to a particular class.

An optimal segmentation schemes for polarimetric land applications has recently (2002) appeared [24]. This method uses simulated annealing, and consequently the computation time required is significant. An alternative approach, also reported in [24], based on the eigenvalues from polarimetric decomposition, offers an alternative approach for a much lower computation time.

Several segmentation based schemes in the literature, have also been used in hierarchical [12, 25] classification schemes. This means that different features can be applied at each stage of the process. Features based upon segment properties such as shape, size, and parameter variance etc can also be introduced [25]. Features can also be determined at different spatial scales providing a common framework for the segment boundaries is used [25].

If the segmentation is performed jointly with data from other sensors (e.g. other radar platforms or multi-spectral imagery), then information from different sensors can also be included in a classification scheme [12].

The types of hierarchical segmentation schemes described allow different types of information to be used in a complementary manner. However, these schemes are not amenable to a rigorous design procedure leading to the best solution. Comprehensive validations have not been published.

4.4 Recommendations

An important criterion for the selection of the classification techniques for this study was the maturity of the approach. Maturity has been judged to be determined by publications in technical journals (as opposed to conference papers) which provide details of the technique and a quantitative validation. In these respects the following publications were judged to be the most mature:

- For supervised classification, the unified approach described in [21] that uses a maximum likelihood distance measure based on Wishart statistics.

- For unsupervised classification, the approach based on H, alpha cluster initiation [16, 17]

A particular feature of both of these methods is their applicability to *general* scenes; no customisation is required.

The technique described in [10] is a *customised* method for specific applications. It is a mature technique that has been used extensively in practice e.g. for forest survey. A comparison between this and the general techniques is recommended.

5 CURRENT TRENDS IN CLASSIFICATION

A different strategy for polarimetric data classification has recently been proposed in [26], that builds upon concepts originally proposed in 1989 [6], where the scene is classified in terms of fundamental scattering characteristics: single bounce, double bounce and volume scattering. In [26] a further subdivision of the polarimetric feature space using amplitude information. Classification is then performed using Wishart clustering but with constraints on the pixels, according to their initial classification categorisation. The whole procedure is effectively a classification based upon cluster centre seeds originated by a systematic subdivision of the whole polarimetric feature space.

The above technique circumvents several of the criticisms made in section 4. There can be no mixing of classes that are inherently different, and the whole of the polarimetric feature space including both polarimetric *and* amplitude information is uniformly addressed. However, the technique still uses the whole polarimetric covariance matrix, so the question of whether better performance would arise through the use of independently weighted features (e.g. intensities, correlation, phase) is not addressed.

Further research to validate hierarchical classification techniques is required [27].

6 CONCLUSIONS

The complexity of a scene in terms of the number of classes, the class types and within class variations plays a critical part in the outcome of scene classification. In reviewing validation results these issues need to be borne in mind.

Speckle and within class variations are important factors that reduce classification accuracy. While within class variation may provide some additional information, speckle is solely noise and should be removed as much as is feasible. Speckle reduction techniques that preserve boundary features should be used. The extent to which any within class variations should be recognised depends on the user application requirements.

Both speckle reduction and classification can be performed at a pixel level or on segments (i.e. regions containing pixels that have in some sense similar properties). Pixel level methods are most widely reported. Pixel level classification is suitable for statistical assessment of scene properties. Since segmentation defines objects with boundaries, it is more directly suited to the provision of mapping information. Pixel level classifications can be segmented. A region based classification, as is provided by segmentation, might provide a statistically more optimal use of data.

There are two approaches to the use of fully polarimetric data for classification. These are methods that use the whole signature, and methods that use specific features derived from parts of the full signature. Methods that use the whole signature use the covariance or coherency matrix data. The methods that use specific features are customised methods. Here the features can be different types of information e.g. intensity, coherence, phase difference. It is clear that phase information does play a key part in classification (particularly through arg (HHVV*) which allows the key types of scattering mechanisms to be distinguished). Although all the information is in the fully polarimetric data, it may be presented in a suboptimal way through the use of general features such as the covariance matrix. It is not reported whether or not customised methods out perform the generalised methods.

There are two approaches to classification: unsupervised and supervised classification. In principle the unsupervised approach should show the scene classification that is supported by the sensor. However, unsupervised classification requires the specification of an initial classification, and successful convergence depends on a good initiation. Validated techniques for class management (creation and splitting) are required. Supervised classification requires the user to specify specific classes of interest. This method only works well if the classes are pure, well separated and invariant over the image. If this is not the case, errors will be built into the classification process. In both unsupervised and supervised classification prior knowledge is required. A joint use of both strategies is generally required.

In complex scenes, class ambiguities are likely to be inevitable. These can only be resolved by introducing further information. This includes non radar information (e.g. shape and size of regions), information on different spatial scales, scene context and information from other sensors. This is likely to involve hierarchical classification techniques.

For this study mature techniques were required; mature techniques were defined to be those that have been validated and published in a journal (as at November 2002). Accordingly the generalised signature approach [16, 21] to classification was recommended. Comparison of these with the customised method of [10] was also recommended.

7 REFERENCES

1. Rodrigues A., Corr D. G., and Hoekman D., Assessing the benefit of SAR polarimetry for land cover classification, POLinSAR 2003, 2003
2. Ferro-Famil L., Corr D. G., Rodrigues A., Pottier E. and Rodrigues A., Statistical segmentation of polarimetric SAR data, POLinSAR 2003, 2003
3. Rodrigues A., Corr D. G., and Partington K., Unsupervised Wishart classification of sea-ice using entropy, alpha and anisotropy decompositions, POLinSAR 2003, 2003
4. Cloude S. R. and Corr D. G., Tree-height retrieval using single baseline polarimetric interferometry, POLinSAR 2003, 2003
5. Ulaby F. T. and Elachi C., Radar polarimetry for Geoscience applications, *Artech House* 1990
6. Van Zyl J. J., Unsupervised Classification of Scattering Behaviour Using Radar Polarimetry Data, *IEEE Transactions on Geoscience and Remote Sensing*, Vol 27, No 1, 36-45, 1989
7. Zebker H. A., and van Zyl J. J., Imaging radar polarimetry: a review, *Proceedings IEEE*, Vol 79, No 11, 1583 – 1606, 1991
8. Cumming I. G., and van Zyl J. J., Feature utility in polarimetric radar image classification , *IEEE IGARSS 89*, 1841 – 1846, 1989
9. Van der Sanden J. J. and Hoekman D. H., Multiband polarimetric SAR in support of tropical forest resources assessment, *IEEE IGARSS '95*, Vol 2, 1207 - 1209, 1995
10. Hoekman D. H. and Quiriones M. J., Land cover type and biomass classification using AirSAR data for evaluation of monitoring scenarios in the Columbian Amazon, IEEE Transactions *on Geoscience and Remote Sensing*,, Vol 38, Issue 2, Part 1, March 2000, pp. 685-696
11. Lee J. S., Grunes M. R. and Kwok R., Classification of multi-look polarimetric SAR imagery based on complex Wishart distribution, *International Journal of Remote Sensing*, Vol 15, No 11, 2299 – 231, 11994
12. Dobson M. C., Pierce L. E. and Ulaby F. T., Knowledge based land-cover classification using ERS-1/JERS-1 SAR composites, *IEEE Trans Geoscience and Remote Sensing*, Vol 34, No 1, 83 – 99, 1996
13. Cameron W. L., Leung L. K. and Youssef N. N., Simulated polarimetric signatures of primitive geometrical shapes, *IEEE Transactions on Geoscience and Remote Sensing*, Vol 34, No. 3 , 793 – 803, 1996
14. Cloude S. R. and Pottier E., A review of target decomposition theorems in radar polarimetry, *IEEE Transactions on Geoscience and Remote Sensing*, No 2, vol. 34, March 498 – 518, 1996
15. Cloude S. R. and Pottier E., An entropy-based classification scheme for land applications of polarimetric SAR data, *IEEE Transactions on Geoscience and Remote Sensing*, Vol 35, No 1, 68 – 78, 1997
16. Ferro-Famil L., Pottier E. and Lee J. S., Unsupervised classification of multifrequency and fully polarimetric SAR images based on the H/A Alpha - Wishart classifier, *IEEE Transactions on Geoscience and Remote Sensing*, Vol 39, No 11, 2332 – 2342, 2001
17. Lee J. S., Grunes M. R., Ainsworth T. L., Schuler L. J. and Cloude S. R., Unsupervised Classification using Polarimetric Decomposition and the Complex Wishart Distribution, *IEEE Transactions on Geoscience and Remote Sensing*, Vol 37/1, No. 5, 2249 – 2259, 1999
18. Lee J. S., Grunes M. R. and de Grandi G., Polarimetric SAR speckle filtering and its implications for classification, *IEEE Transactions on Geoscience and Remote Sensing*, Vol 37, No 5, 2363 - 2373, 1999
19. White R. G., A simulated annealing algorithm for SAR and MTI image cross-section estimation, *SPIE Proceedings*, Vol 2243, 231 – 241, 1994
20. Schou J. and Skriver H., Restoration of polarimetric SAR images using simulated annealing, *IEEE Transactions on Geoscience and Remote Sensing*, Vol 39, No 9, 2005 – 2015, 2001

21. Lee J. S., Grunes M. R. and Pottier E., Quantitative comparison of classification capability: fully polarimetric versus dual and single-polarisation SAR, *IEEE Transactions on Geoscience and Remote Sensing*, Vol 39, No 11, 2343 – 2351, 2001
22. Chellappa R. and Rignot E., Segmentation of polarimetric synthetic aperture radar data, *IEEE Transactions on Image Processing*, , Vol 1, No 3 , 281 – 300, 1992
23. Freeman A. and Durden S. T., A Three Component Scattering Model for Polarimetric SAR Data, *IEEE Transactions on Geoscience and Remote Sensing*, Vol. 3, No 3, 963 – 973, 1998
24. Lombardo P. and Oliver C. J., Optimal classification of polarimetric SAR images using segmentation, *IEEE Radar Conference, 2002*, 8 –13, 2002
25. Benz U. and Pottier E., Object based analysis of polarimetric SAR data in alpha-entropy-anisotropy decomposition using fuzzy classification by eCognition, *IEEE IGARSS 2001*, 2001
26. Lee J. S., Grunes M. R., Pottier E. and Ferro-Famil L., Segmentation of polarimetric SAR images that preserves scattering mechanisms, *EUSAR 2002*, 2002
27. Corr D. G., Benz U., Lingenfelder I., Walker A. and Rodrigues A., Classification of urban SAR imagery using object oriented techniques, *IEEE IGARSS 03* , – To be published.